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DRIVE-DEFENDER: A Driver Safety-oriented Alcohol and Drowsiness Detection System

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Abstract

DRIVE-DEFENDER presents a pioneering approach in driver safety through the development of a real-time machine learning system for alcohol detection. The detrimental impact of alcohol-impaired driving on road safety necessitates efficient detection mechanisms. Current methodologies are often hindered by their cost, invasiveness, and reliance on specialized sensors. DRIVE-DEFENDER utilizes a camera for recording the face of the driver in real time, employing image processing techniques to identify facial landmarks. These landmarks serve as inputs for the calculation of features indicative of alcohol impairment, such as changes in facial expression and coordination. Machine learning algorithms, coupled with adaptive thresholding mechanisms, enable accurate detection of alcohol intoxication without the need for expensive hardware or causing distractions to the driver. The proposed approach offers a cost-effective, non-intrusive solution for enhancing driving safety in real-time by promptly identifying and mitigating the risks associated with alcohol-impaired driving.

Keywords: Fatigue, safety of drivers, aspect ratios for the eyes and mouth, head pose estimation, computer vision, image processing, detection of alcohol consumption, drowsiness detection

INTRODUCTION

In the realm of driver safety, the prevalence of accidents stemming from alcohol impairment and drowsiness remains a critical concern. The World Health Organization (WHO) estimates that crashes involving cars and trucks claim the existence of a total of 1.35 million individuals each year., with alcohol consumption being a significant contributing factor [1, 2]. Additionally, fatigue-related crashes are estimated to account for a considerable portion of road accidents globally, emphasizing the urgency for effective drowsiness detection systems [3]. This research article discusses DRIVE-DEFENDER, an original work on driver safety-oriented system, designed for both alcohol and drowsiness detection. Leveraging advancements in machine learning and image processing technologies, DRIVE-DEFENDER offers a real-time solution for identifying signs of impairment and fatigue in drivers. By utilizing non-invasive methods such as facial landmark recognition and eye aspect ratio calculation, the system can accurately assess driver condition without the need for specialized sensors or intrusive devices.

Safety on the road is significantly threatened by fatigue. Microsleep-induced drowsiness in drivers often results in catastrophic accidents. Drowsiness when driving is typically associated with sleep deprivation, fatigue, or psychological issues. In 2020, the Ministry of Interior in the UAE documented a total of 2931 automobile collisions. The total number of files increased to almost 3487 in 2021. The majority of these collisions were

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ascribed to driving while distracted, resulting from driver fatigue, abrupt lane changes, or inadequate vehicle spacing [4]. It is imperative to utilize emerging technology in order to strategize and develop systems capable of monitoring drivers and assessing their level of attentiveness whilst driving. Researchers from throughout the world have developed driver drowsiness detection (DDD) systems to identify indicators of driver sleepiness in the early stages, since a lot of countries are worried regarding this matter. Drowsiness detection techniques can be divided into three different categories based on the measurements, according to the literary works employed to identify indicators of tiredness [1, 5–7]: applications based on biology, vehicles, and images. Among the first biologically based measurements under the heading of psychological indicate monitoring are electroencephalograms (EEGs), blood pressure, electrocardiogram, electrocardiogram, and electrooculogram commands [8, 9, 10]. Sleepiness in this kind of setup is determined by identifying the message's departure from the characteristics of the normal status and assessing whether the newly acquired signal accurately reflects fatigue. In the following category, measures based on machinery rely on multiple sensors that are equipped to measure different vehicle and street data to track variations in the patterns of vehicle movement. Vehicle-based technologies look at changes or unusual behavior of the car, such as the wheel's position, acceleration, or range deviation, to determine the degree of tiredness [11, 12]. The last category consists of visual measurements, that primarily depend on the driver's face and forehead for signs of tiredness. By observing the motions of the driver's head and facial features, including their pupils, crests, eyebrows, and breathing, these gadgets detect when a motorist is sleepy [13–15].

Every one of the three groups has certain restrictions [6, 15]. Biologically oriented methods are able to detect sleepiness at the earliest phases because of their capacity to detect the continual changes in the signals generated by the body, nevertheless, for the majority of biological-based structures, the condition is needed recommended the driver's physique be fitted with conductors. For most drivers, this arrangement is awkward and undesirable. Additionally, this includes disturbance which degrades the precision of the message. Car-based technologies are largely dependent on the type of automobile, and they can be significantly impacted by a number of variables, such as road characteristics, weather, and the driving skills, expertise, and behaviors of the operator [16–19]. The resolution of the lens used and how well it adjusts to different lighting circumstances are major factors in the restrictions of based on pictures solutions. Objects that cover off areas of the confront, including costumes, spectacles may also affect how accurate graphical DDD methods are. Of all three of these structures, graphical-based systems are thought to be the least intrusive, least expensive, and least impacted by the state of the roadways. As a result, visual-based metrics are frequently used to create DDD systems that are completely lightweight, adjustable, affordable, and instantaneously [5, 12–15, 20–23].

We present a novel based on pictures DDD technique in this work. It takes advantage of a special mix of traits that computer vision extracts from the driver's visual measurements. Due to their low cost we decided to use such methods to make our working model which detects if the driver is drowsy and/or drunk. We accomplish this by mounting a video recorder on top of the panel to watch the motorist's head. Next, we examine the motorist's facial features, including their mouth and eyebrows. Given that the lips and eyeballs are among the most visible features on our bodies, they help determine the mental condition of driver like whether he is sleepy or not. This discovery is important because it could transform safety for drivers by offering an affordable, non-intrusive means of detecting alcohol consumption and drowsiness in real-time. By mitigating the risks associated with impaired driving, DRIVE-DEFENDER has the ability to stop accidents and prevent a great number of deaths while driving [24–26].

The remainder of the document is structured according to the following format: The most recent research on the features used in this study is summarized in the second section [27–32]. The third section explains the process. The outcomes are presented and discussed in the fourth section. The conclusions and suggestions for future planning are covered in the final part.

RELATED WORK

Many scholars from around the world have looked at the topic of driver tiredness identification. Based mostly on the indicators used to indicate sleepiness, the suggested approaches to address the issue can be distinguished from one another [5, 6]. Organic factors are the drowsiness of the driver indicative characteristics that are obtained from the body evidence data such as electroencephalogram, electrocardiogram, and echocardiogram. These characteristics are reliable in detecting fatigue, but they are awkward for the driver because they require the use of sensors attached to the motorist's body [5, 8, 33, 9, 10]. Other often used fatigue indicative elements are dependent on how the car is driven, and information like the control wheel angular measurement and the lane departures is connected to the operator's degree of tiredness. Despite being convenient for the motorist, research indicates that this tactic's reliability is lacking. The final set of indicators that indicate tiredness depends on images. Pictures that follow the driver's actions are commonly used to create criteria in order to gather data on the driver's mouth, head, and retinal movements. Since they do not require the driver to link equipment or sensors to their body, they are more practical for drivers than biologically based ones. The most widely used methods for identifying fatigue in drivers are based on image technologies. Several optical behaviors that tired people exhibit can be recognized by using facial characteristics such as their lips, pupils, and forehead. Lenses and other visual sensors can capture such sleepy behaviors. Following that, several characteristics can be identified from this data, and using methods from computer vision, they process it to visually track the motorist's state of health in hopes of non-intrusively detecting sleepiness. Generally speaking, there are three categories into which based on imaging technologies can be placed based on how the head, lips, and eyes move [6, 7]. Studies have made use of several visual elements. They involve the number of blinks, the longest period during which the eyes may close, the proportion of closed lids, the angle of view of the pupils, the shape of the lids, the number of times of blinking, the greatest amount of time the mouth opens, the head position as well the incidence of head smiling, and the analysis of the movement of the cranium. The concatenation of these characteristics has also been taken into account [34–41]. We give a thorough description of each feature utilized in our recommended structure in this subsection. The ocular area provides the most often extracted features utilized based on pictures methods to assess fatigue. The eye activity rating (EAR) [27, 40, 41] was presented by a number of academics as a straightforward metric to detect eye movement from facial signals. It is used to evaluate the level of eye opening. A sudden flash of light is captured when the electroencephalogram value drops suddenly. A sleepiness detection technique based on the EAR measure was developed by Maior et al. [27]. Another study that looked at tiredness as an input for a binary SVM (support vector machine) classifier used the EAR measure. The accuracy of the model's diagnosis of the driver's tiredness was 96.5%. Since mouth expressions offer helpful characteristics for DDD, they are a good indicator of sleepiness. The scientists suggested using mouth movement detection to identify yawning as an indication of drowsiness. They used over one thousand typical photos and a set of twenty yawning shots in their experiment. The driver's mouth was identified by the system using a cascade classifier on the face pictures. A SVM classifier was then used to detect yawning and notify the motorist. An 81% detection rate for yawning was found in the final data. The mouth movement proportion was yet another characteristic based on lips. Mouth aspect ratio (MAR) is another name for it. According to the design, the mouth's expanding motion indicates that a person should go to sleep. An SVM classifier was used to input this feature, and it achieved 97.6% accuracy. Head motions are another important parameter that can be used to diagnose fatigue in image-based systems because they can indicate drowsiness. As such, they can be used to extract properties that are useful for machine learning-based sleepiness identification. These head characteristics include head position as well nodding of the head rate, and head pointing movement. The area of the forehead was used in reference [31] as a starting point to ascertain the driver's head's orientation.

Using a manually compressed face textured description, Moujahid et al. [35] developed a visual-monitoring alertness monitoring technique that captured some of the most noticeable indications of fatigue. The three indicators of drowsiness—head nodding, frequency of yawning, and blinking rate—were first quantified. Subsequently, to achieve simplicity, researchers employed picture modeling in pyramidal multiple layers with distinctive filtration. They ultimately used a non-linear SVM classification algorithm, which produced results with a precision of 79.83%.

Four deep learning models are used in the driver vigilance detection framework presented by Dua et al. [16]. These models are taken from the driver's video materials, which consist of emotions, head, word, and eye motions, as well as wrist and body movements. The four deep learning models were fed driving film simulations as input. After the four models' outputs were fed into a SoftMax classifier using a simple averaging ensemble approach, the overall accuracy was 85%.

PROPOSED METHODOLOGY

In order to recognize if a driver is intoxicated and/or tired we need to first detect a face and then do analysis on facial features like eyes and lips. Additionally, in "Drinking and Social Transmission: A Study of the Transmission of Happiness in Parties of Men and Women Drinkers," we can notice which intoxicated people tend to smile more often therefore by glancing at the drivers mouth we tell if the person has been drinking. In order to accomplish this analysis, we make use of dlib 68-point face mask. After evaluating the driver's face, we can tell if they are in fit condition in order to drive. We undertook live analysis by using a webcam positioned in a car. The flowchart of the system can be seen in Figure 1.

Detecting Sleepiness

A face characteristic that is highly significant is its symmetry. We utilized a one-dimensional indication having an aspect ratio equal to the image's lengths in order to represent the degree of symmetry in a digital image. This gave us the number that indicates where the vertical axis of balanced items is located within the structure [42–45]. The standard method for calculating the signal of symmetry involves increasing the quantity in the space between both these images by accumulating matrices for each pair of white photons that are on a single row. The technique is used having a border image, which we designate as a white dot (the pixel having quantity 1). By applying a set of concepts to provide an improved computation of the symmetrical face, we make advances on the symmetrical computation approach into a picture and then apply it to the recognition of faces. The ratio of symmetry is calculated within two frames (Z1 and Z2) rather than between two white pixels in the image.

Detecting Drowsiness

Detecting drowsiness needs you to detect the driver's eyes. For that reason, we make use of make use of dlib's face feature detection a. The frequency distribution of oriented gradients (HOG) feature, which is now extensively used, is further combined with a linear classifier, an image pyramid, and finally a sliding window detection strategy to make this face detector. In Figures 2 and 3, the location of 68 coordinates (x, y) that map the facial points on an image of a person's face can be seen. The landmarks are estimated using the pre-trained facial landmark's facial detector using dlib these landmarks can be seen. The iBUG 300-W dataset was used to train the dlib facial landmark predictor. It is to be noted that there are various other facial landmark detectors which can be used to detect faces—such as the 194-point model that can be trained using the HELEN dataset. Regardless of the dataset the same dlib framework can be used to train a shape predictor on the input data.

Eye Aspect Ratio (EAR)

Six (x, y) dimensions are used to indicate each eye. If you were looking at the individual directly, you would begin at the leftmost point of the pupil and work your way clockwise round the remaining area. These coordinates' width and height are related to one another. According to the work of Soukupová and Čech in their 2016 article, "Real-Time Eye Blink Detection Using Facial Landmarks" we can create a formula that captures this relation, also known as the eye aspect ratio, which is shown in Figure 4.

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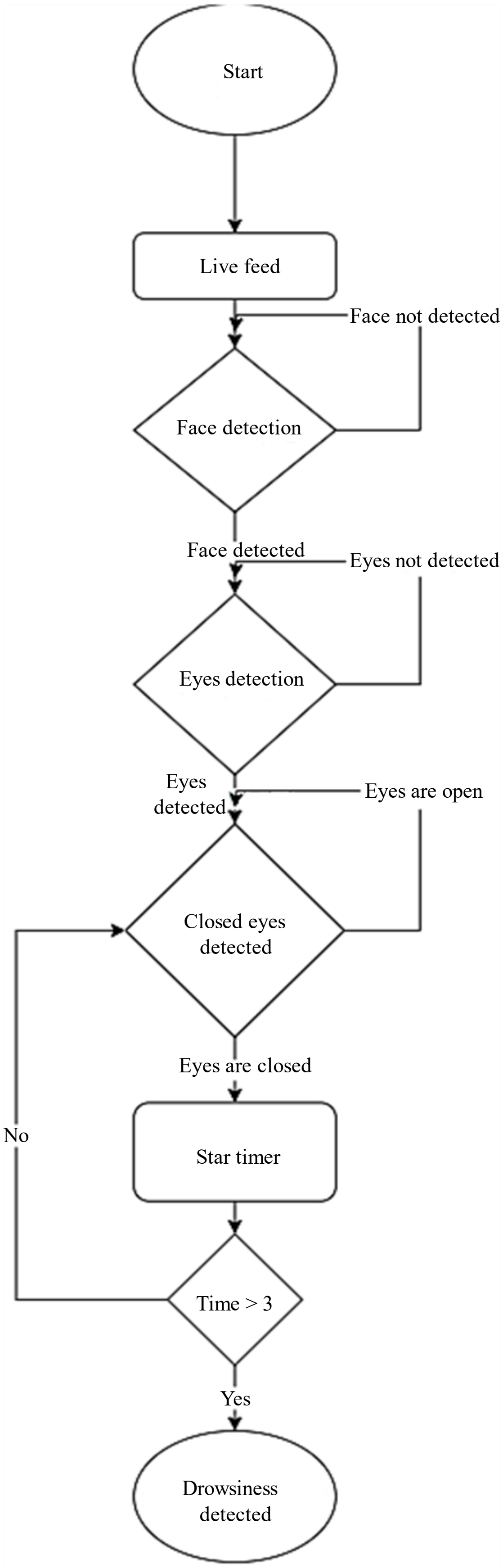

Figure 1. Flowchart of the system.

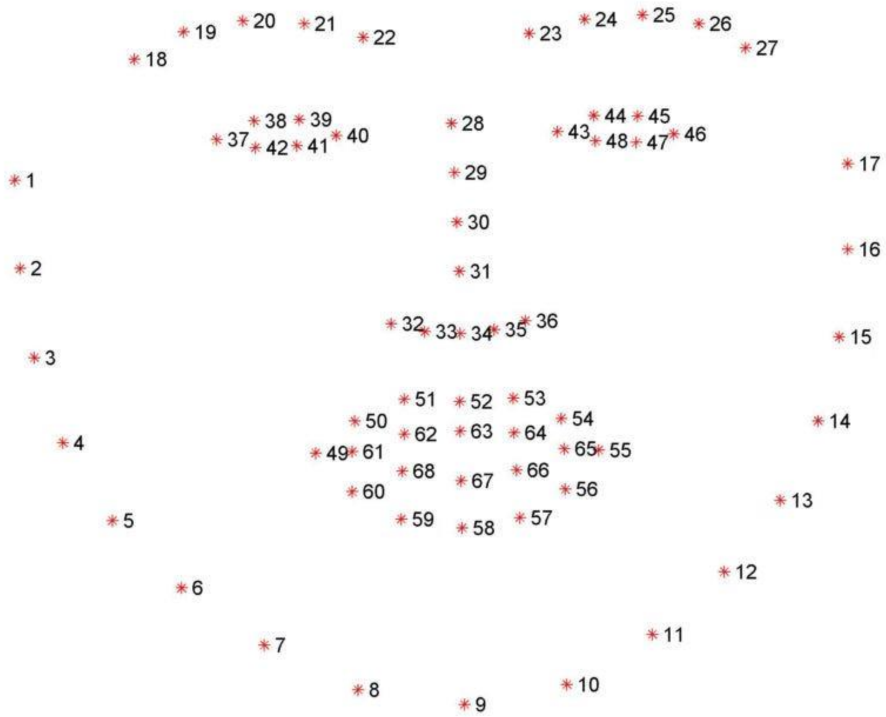

Figure 2. Facial landmarks.

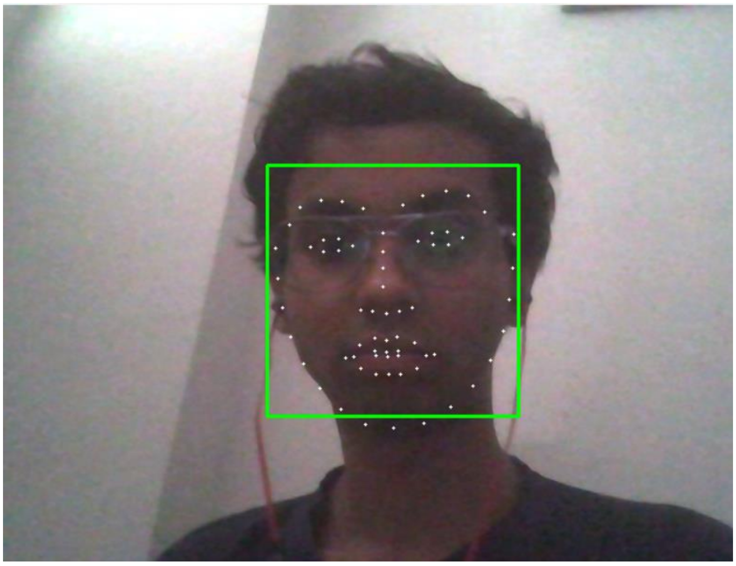
Figure 3. Facial landmarks in real time.

$$\text{EAR} = \frac{\|p_2 - p_6\| + \|p_3 - p_5\|}{2\|p_1 - p_4\|}$$

Figure 4. Equation for eye aspect ratio (EAR).

When an eye is open, the ear is for the most part constant, and if it is closed, it is close to zero. It has an insensitive head position and is partially human. The open eye's proportion differs slightly between people but remains entirely unaffected by the picture's homogeneous scaling and the face's in-plane movement. Because both pupils move simultaneously the average ear response is taken from both of them. Utilizing this simple formula, we may determine whether someone is blinking without the need for picture processing and by simply utilizing the percentage of ocular marker ranges as shown in Figure 5.

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Figure 5 shows us the locations of the eyes' markers when they are opened. Pupil locations when the eye shuts down, the top-right. At the bottom: a temporal plot of the EAR is shown. According to Soukupová and Čech, (Figure 6), a blink is indicated by the fall in the optical proportion.

Emotion detectors are utilized in many industries, one being the media industry where it is crucial for the firms to determine the public reaction to their products. The basic emotion detection consists of evaluating the geometry of one’s facial landmarks. In the event of a smile, the distance between the corners of the lips grows. However, as different persons have varying mouth widths, one may normalize this measure by dividing it by the jaw distance and produce a generic ratio that can be utilized with diverse participants. Once we detect the facial landmarks, we can obtain the coordinates via (landmarks [0] parts () [i].x, landmarks[0].parts()[i].y), where i is the index, to calculate this ratio In our basic detector, as shown in Figures 7 and 8.

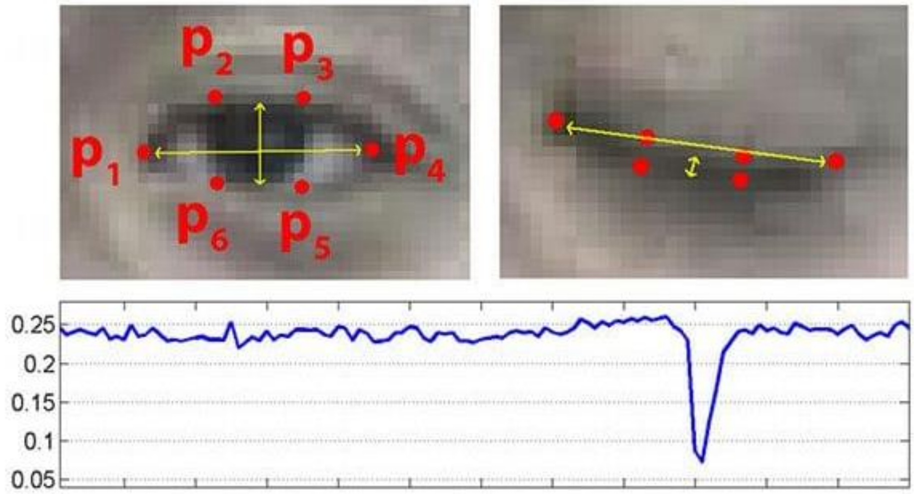

Figure 5. Eye aspect ratio (EAR) change over time.

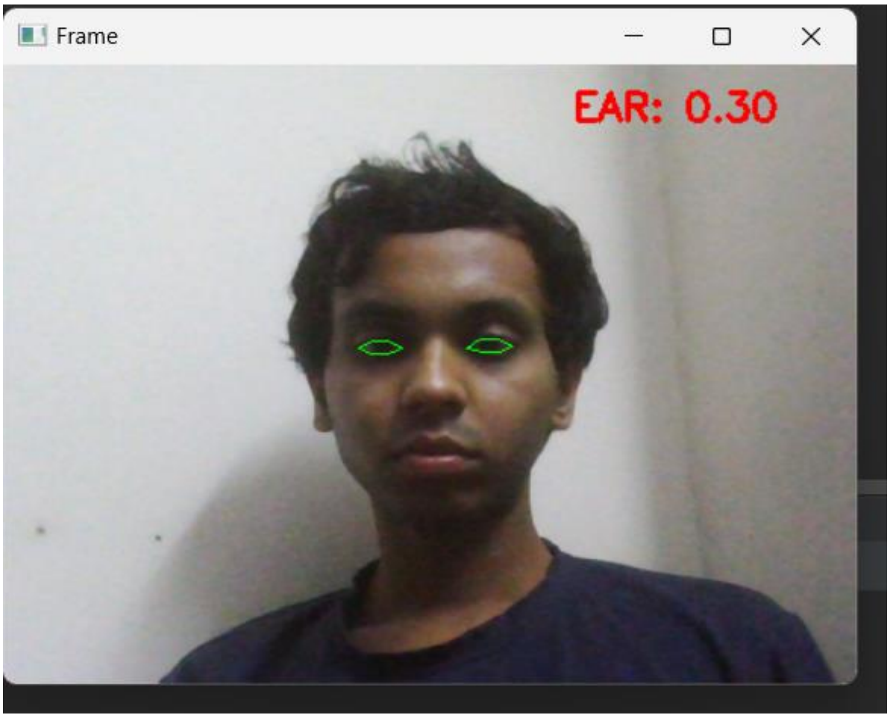

Figure 6. Eye close detected.

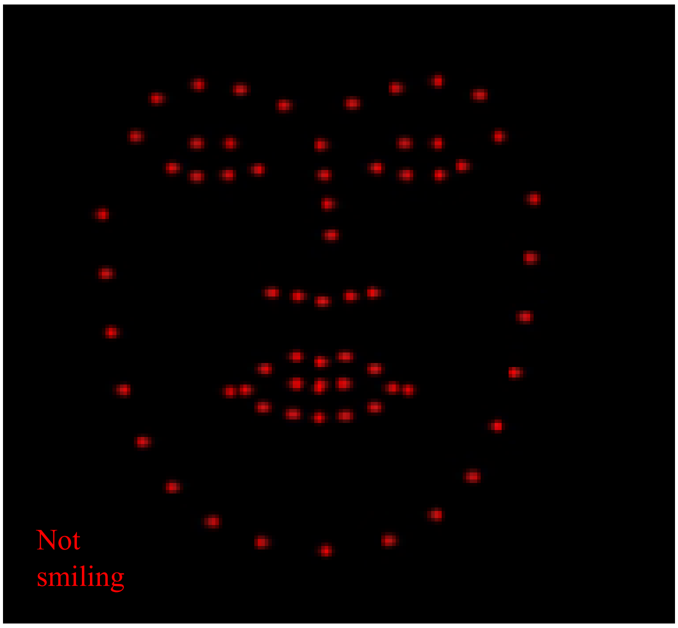

Figure 7. Facial landmarks not detecting a smile.

Figure 8. Facial landmarks detecting a smile.

EXPERIMENTAL RESULTS

The system can detect drowsiness, as shown in Figure 9 and 10, based on image recognition shows that the drowsiness system can identify signs of tiredness at an early stage. The system has trouble detecting if the driver is intoxicated or not.

Table 1 shows us different methods of applying image processing to detect drowsiness. These methods were proposed by various authors across the globe. Here we can see that these methodologies mainly use the eyes and mouth of driver to detect drowsiness. Table 2 shows the results of the proposed system when tested in real life. The results show that the system can detect drowsiness well but has trouble detecting drunkenness of the driver. We can also see that the system has problems when used under bad lighting conditions.

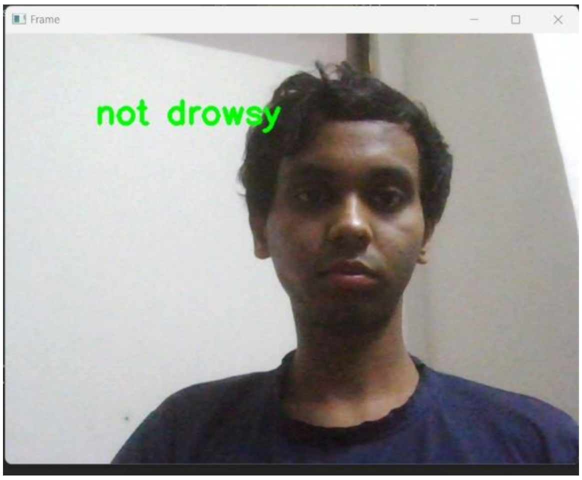

Figure 9. The system accurately detects open eyes.

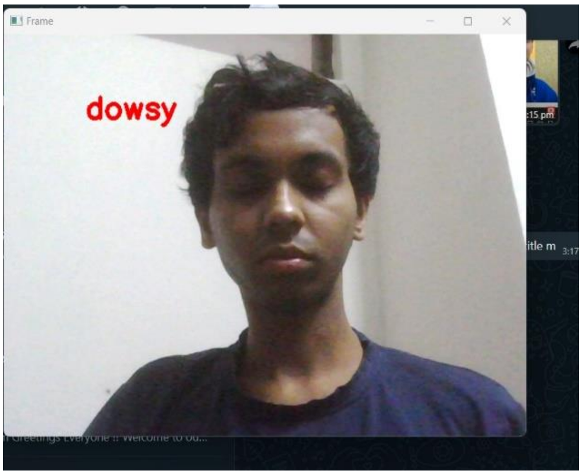

Figure 10. The system accurately detects closed eyes.

Table 1. Different methods of drowsiness detection using image processing.

Reference	Image-Based Parameters	Features	Description of Methodology
39	Eye	Rate of blinking	The frequency of eye closures within a defined timeframe.
40	Eye	Maximum duration of eyes closed	Identifying the maximum duration of eye closure is crucial, yet delaying detection of prolonged closures poses risks, especially when indicating drowsiness in a driver.
41	Eye	Percentage of eyelid closure	The duration within a minute when the eye is 80% closed or more.
42	Mouth	Yawning frequency	The frequency of mouth openings within a defined timeframe.
43	Head	Head pose	The driver's head movements, measured by identifying video segments where there is a noticeable change in three Euler angles that represent head poses like: nodding, shaking, and tilting.
44	Face	Respiration (using thermal camera)	Facial thermal imaging was used to analyse the driver's respiration patterns and look for connections with the driver’s drowsiness levels.
45	Mouth movements, head, or eyes	Facial expressions, behavioral characteristics, head movements, and hand movements	An architecture that used four distinct deep learning models to extract four different types of features from the driver’s face, eyes, and hand movements.
Proposed methodology	Eye, mouth	Eye aspect ratio and mouth aspect ratio	Eye aspect ratio (EAR) effectively detects instances of eye closure. EAR serves as an indicator of the degree of eye openness. If the eyes are closed, the EAR value drops to zero, whereas it remains relatively constant when the eye is not closed.

Table 2. Results of system when tested in real life in different environments.

S.N.	Eyes				Alcohol	
	Good lighting		Bad lighting			
	Actual	Predicted	Actual	Predicted	Actual	Predicted
1	Open	Closed	Open	Closed	Drunk	Not drunk
2	Closed	Open	Open	Open	Not drunk	Drunk
3	Open	Open	Closed	Open	Drunk	Drunk
4	Closed	Closed	Closed	Open	Not drunk	Drunk
5	Open	Open	Open	Open	Drunk	Not drunk

CONCLUSION

A real-time drinking and drowsiness system is presented. We showed different facial features that one needs to look at to determine whether the motorist is fit to drive on their own. This system can accurately tell if the driver is drowsy but cannot guarantee if the driver is intoxicated by just looking at their face. Since it does so by seeing if they are smiling or not, which may not accurately correlate with their blood alcohol level all the time. The system can be improved if one uses alcohol sensors in the car, like mq3 sensors to determine the alcohol content present in the car or by measuring the person's pulse, temperature and other measurements using detectors mounted on the driving column. These results of alcohol detection will improve if these methods are used. However, these require additional hardware whereas if one must make a judgement on a driver's level of intoxication by using a camera only, the proposed method will suffice.

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